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UTILISING CNN AND LSTM FOR NUTRITIONAL DEFICIENCIES IDENTIFICATION IN GRAPE PLANT LEAVES

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Abstract-- In order to compensate for soils that are deficient in certain minerals, contemporary fertilisation techniques look for signs of nutritional deficiencies in plant leaves. In order to create a fertilisation strategy that supplies the vital micronutrients without overproducing others, it is important to determine the amount of vitamins and minerals that will be required. In agriculture, nutritional deficiencies are indicated by plant leaves. It is possible to physically examine these leaves from the plant's morphological components, which gives enough information to identify the nutritional shortage. The primary objective of this study was to identify nutritional deficiencies in grape plant leaves. In this research, we use Convolutional Neural Networks (CNNs) for model training. By feeding the model's output into an LSTM, we can classify the images of grape plant leaves as either healthy, N-deficient, Fe-Deficiency, P-Deficiency, Mn-Deficiency, K-Deficiency, Zn-Deficiency, Ca-Deficiency, B-Deficiency, Mg-Deficiency, or S-Deficiency. Accuracy measures the model's performance. Data analysis revealed that the suggested model had an accuracy rate of 98.6 percent. These results suggest that convolutional neural networks (CNNs) might be useful for identifying nutritional deficits in grape plant leaves.

Keywords: Grape plants, Boron Deficiency, Iron Deficiency, Agriculture, Deep Learning, Fertilization.

I. INTRODUCTION

Since plants may suffer significant harm and output losses due to an excess or deficiency of vitamins and minerals, accurate nutritional evaluation of plants is an important component of agricultural business management. According to the latest agricultural standards, correct nutritional analysis has the potential to avert these losses and provide the framework for the responsible administration of dietary supplements. This way, we can save money and reduce our impact on the environment. Additionally, decision-support and agricultural administration platforms may include computational methods for plant vitamin and mineral monitoring, which may be very useful for agricultural workers who do not have access to professional assistance. The capacity of CNNs to analyse complicated data patterns and provide predictions using both historical and real-time data is a boon to prediction jobs. In order to capture hierarchical characteristics, a CNN may use several layers of hidden units. Estimates of the task's completion probability will be provided by the CNN using the real-time data sources. It may be used for both short-term and long-term forecasting. Regardless of the situation, CNNs are useful because of their adaptability and ability to recognise complicated, non-linear relationships in the data. Therefore, remember that high-quality data, domain knowledge in task behaviour, and the chosen model are all necessary for developing a reliable CNN-based prediction system [1]. Image recognition, anomaly detection, natural language processing (NLP), autonomous vehicles, energy forecasting, recommendation systems, manufacturing and quality control, financial forecasting, robotics, marketing, and customer analytics are just a few of the many applications of convolutional neural networks (CNNs), a type of artificial neural network. Additionally, CNNs can sift through mountains of data collected by sensors and satellites to foretell future weather patterns, environmental impacts, and climate change. Many different kinds of forecasting tasks may benefit from CNNs because to their adaptability and ability to handle complicated data sources. However, CNNs may be difficult to construct and need a lot of computer power and training data. When deciding to use CNNs, it is important to consider the specifics of the current prediction issue [2].

II. RELATED WORKS

Many popular approaches, including CNNs, Multi-Layer Perceptrons (MLPs), and K-Nearest Neighbours (KNNs), have failed to reliably identify nutritional deficiencies in plant leaves. In order to detect nutritional deficits in the plant, several research used Deep Learning (DL) and Machine Learning (ML) [3]. Farmers in less developed nations sometimes fail to appreciate the importance of fertiliser applications. Therefore, farmers have a hard time identifying soil nutritional deficiencies in the early stages of development. The result is a precipitous decline in agricultural output. Thus, using AI, ML, and deep learning to the early diagnosis of vitamin deficiencies may be fruitful. Agricultural experts discovered that the present procedures cause nutritional deficiencies in plant leaves. In order to identify nutrient deficiencies in plants, researchers now used biological, non-biological, and manual diagnostic techniques. When measuring micronutrients in plant leaves that are not absorbed, visual colorimetry is an easy and well accepted technique. Following extensive research and analysis, this method is often used to assess crop shortages of essential elements including P, N, and K. Plant colour criteria are now the gold standard for estimating a plant's nutritional value, although these evaluations lack scientific rigour. It takes time and effort to use certain procedures to correctly grasp the data, but diagnostic laboratories that analyse nutritional shortfalls and leaf diseases are necessary for more reliable assessments. There are readily accessible alternatives for certain nutrients; for example, a chlorophyll metre may be used to estimate nitrogen, but it is time-consuming and the results aren't always correct. As a result, a lot of work has gone into developing new ways to identify and quantify nutritional issues in crops [4]. Numerous feature extraction and categorization methods have been used in the many studies of nutrient shortages in plant leaves. The project, which included agricultural studies, had as its aim to help farmers increase the quantity and quality of their crops. Table I provides an overview of the current approaches to nutritional deficits in plant disorders.

TABLE I. AN EVALUATION OF CURRENT APPROACHES TO NUTRIENT DEFICIENCIES IN PLANT LEAVES

Research	**Technique**	**Performance metric**	**Disadvantages/Open challenges**
[5]	CNN	Resnet 152 claims an accuracy of 89.07%. 84.94% is Resnet 50's accuracy.	This experiment focused only on one nutritional deficit, namely nitrogen shortage in rice plant leaves.
[6]	Random Forest	Classifier accuracy for categorising nutritional deficits in leaves of coffee plants is 67.5%.	The amount of nutritional deficiencies may have affected the classifier's performance, as coffee leaves sometimes display many deficits simultaneously.
[7]	CNN	DenseNet121 gives a 91.77% accuracy. DenseNet169 and MobileNet have 93.33% of accuracy.	Not even hyperparameter adjustment of ML was taken into account. Just three nutrient deficiencies—nitrogen, phosphorus, and potassium—were taken into account in the rice plant's leaves.
[8]	SVM	Classifying nutritional deficits in maize plant leaves yields an accuracy of 80%.	N, P, and K shortages were the only ones taken into account while analysing maize plant leaves. The precision is poor. To improve the SVM model's accuracy, it is possible to combine optimum parameters.
[9]	MLP	Classifying nutritional deficits in black gramme plant leaves with an accuracy of 88.33% is obtained.	The precision is poor.
[10]	CNN	In terms of identifying nutritional deficits in banana plant leaves, the attained accuracy is 87.89%.	More time is needed for training. In current era of industry, when mobility is paramount, this issue can only be resolved by developing novel, lightweight solutions.
[11]	CNN	When it comes to identifying nutritional inadequacies in groundnut plant leaves, the attained accuracy is 94.64%.	It need additional time for training. More lightweight approaches are needed to circumvent this problem, since modern electronics are mobile in order to operate in the industrial age. Three nutrient deficiencies—nitrogen, phosphorus, and potassium—in groundnut plant leaves were the only ones taken into account.
[12]	Random Forest	In identifying nutritional deficits in cabbage plant leaves, a classification accuracy of 95.5% was attained.	Concurrent symptoms for the same vitamin, the delayed onset of symptoms, and variances within the class all make nutrient insufficiency identification more difficult.
[13]	CNN	When it comes to identifying nutritional deficits in black gramme plant leaves, the attained accuracy is 48.33%.	There is an issue with low precision. To further improve the classifier's performance, we would additionally take into account the effects of younger or longer-lived leaves on the manifestations. When two or more nutrients are absent, it is necessary to conduct an examination.
[14]	Random Forest	In identifying nutritional deficits in cabbage plant leaves, a 98.30% accuracy rate was attained.	There was a lot of red tape since different symptoms of vitamin deficits tended to overlap. In this case, both P-deficit and K-deficit might lead to necrosis. The slow onset of symptoms, variations within the class, and different presentations of the same component make it difficult to identify nutritional insufficiency.
[15]	KNN	Researchers looked at how severely grape leaves were deficient in potassium. A deficit ratio of 93.19 percent is reached on average.	Research on grape leaves has focused on a single nutritional shortfall, namely K-deficiency.

III. PROPOSED METHODOLOGY

The approach used in this study is shown in Figure 1. In this effort, a dataset was self-built. Starting with the self-built dataset, the work follows a technique. Using the dataset one has created, the training set is constructed. Building the model uses eighty percent of the dataset's data. Tests of the model are conducted using the remaining data from the dataset. Eighty percent of the data are used to train the CNN-LSTM model once the training set is constructed. Building testing sets was completed using the remaining 20% of the dataset's data. We verify the test data using the CNN-LSTM network and get the prediction outcome. Changing each hyperparameter setting yields, analyses, and interprets the prediction result. In this study, learning rate and Optimizer are the hyperparameters.

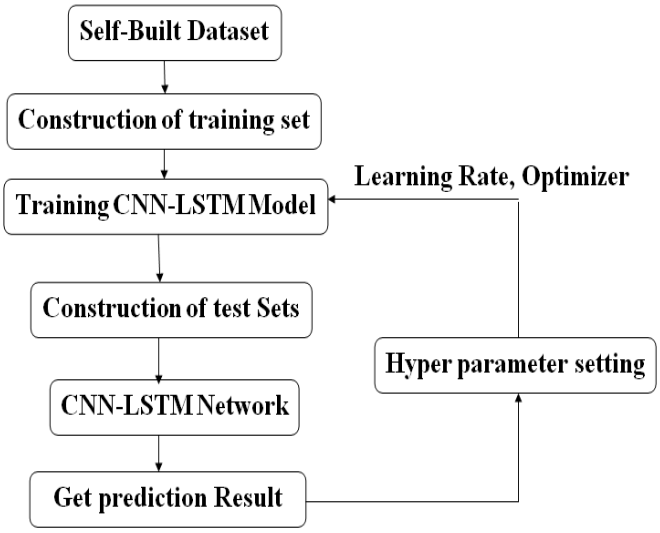


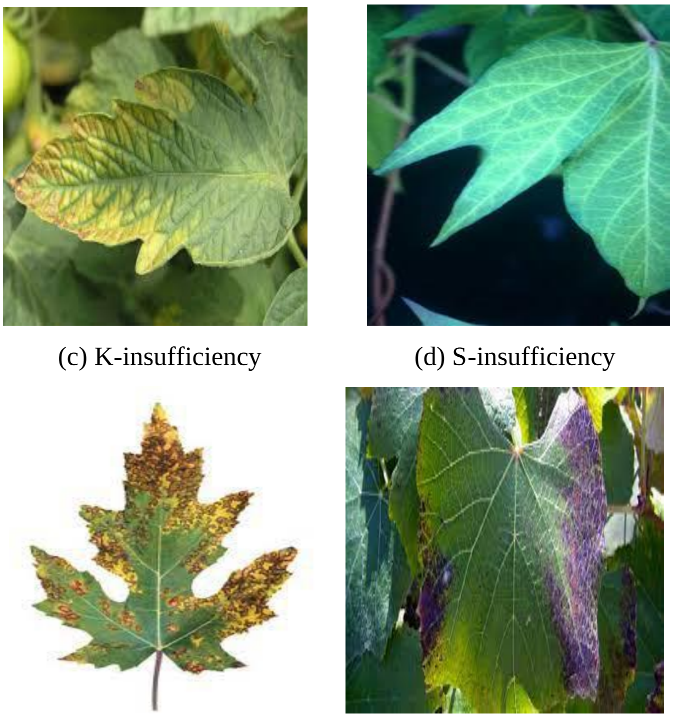
Fig. 1. System architecture proposal

A. Dataset

In plant nutrition, nitrogen, phosphorus, potassium, calcium, magnesium, sulphur, iron, manganese, zinc, and silicon are the ten main groups of nutrients that plants often lack. To put it simply, these are the most important nutrients for plants. Thus, it will be beneficial for farmers to concentrate on identifying these vital plant elements so that they may detect nutritional shortages early on. Six categories of dietary inadequacies were the only ones taken into account in this study. In addition to pictures of healthy leaves, we only looked at six types of nutritional deficiencies: N, P, K, Ca, Mg, and S. Figure 2 shows the range of pictures included in the collection, including healthy leaves, leaves with N, P, K, Ca, Mg, and S deficiencies. For data-driven investigations to be conducted, it is essential to have access to trustworthy datasets. In this project, photographs of grape nutrient shortages collected from farms were used to detect nutritional inadequacies. Images of 1095 grape plant leaves, grouped into seven categories as given in Table II, make up the dataset. Only 20% of the images were used for testing purposes; the other 80% were used for training. The 1095 photographs were randomly split into two sets: one for the training set, which consisted of 876 pictures, and another for the testing set, which had 219 pictures. All of the images in the collection were shot in bright, artificial lighting.

(a) N-insufficiency

(b) Mg-insufficiency



(c) K-insufficiency (d) S-insufficiency

(e) Ca-insufficiency (f) P-insufficiency

Fig. 2. Photos of leaves associated with dietary deficits in the database

TABLE II. DATASET INFORMATION

Class	Total Images	Image count for training purposes	Image count for testing purposes
Healthy	160	138	22
N	159	135	24
P	151	113	38
K	157	116	41
Ca	155	126	29
Mg	158	125	33
S	155	123	32

B. Data preprocessing

For further analysis and computer vision applications, picture segmentation was used to isolate the plant leaves from the backdrop. Because the sun's rays changed during the picture-gathering process, the photographs were shot in a range of lighting conditions, making infield image segmentation a formidable challenge. Accurate image segmentation would be challenging with varying light intensity using current segmentation approaches. Consequently, the KNN model is a potent segmentation method due to its very accurate performance. The KNN model was used for picture segmentation. In this study, no data augmentation techniques were used. The distortion is removed and smoother photos are provided by means filtering. By approximating the values of neighbouring pixels and replacing them with each pixel's value, the mean filter smooths out the image's pixel values, making them less erratic.

C. Data Augmentation

After the pre-processing is complete, the data augmentation operation may be executed. The quality of each training set is improved at each fold. By modifying and increasing the training data, augmentation prevents each fold from being overfitted throughout the training phase. Augmentation significantly affects training results by reducing overfitting of the CNN model during model training. This is due to the fact that data augmentation twice the input image size, increasing the amount of data needed for training. Data augmentation refers to the process of expanding the original data set in DL by the use of various operations like as flipping, rotating, and so on. In order to construct a DL model, a substantial amount of training data is often required. Data augmentation is essential to expand the dataset as the selected grape leaf dataset has a limited amount of photos. In Table III, you can see the specifics of the dataset after the data augmentation.

TABLE III. EXTRACTS FROM THE DATASET FOLLOWING DATA AUGMENTATION

Class	Original dataset	Augmented dataset
All	1095	2095

D. Construction of Training Set

The CNN-LSTM model was trained using a Kaggle Notebook, which comes with 19.6 GB of storage space, 43 hrs of GPU use, and 16 GB of main memory. K-1 data folds are used for training the model, while the remaining folds are used for assessment. K-Fold cross-validation is the name of this method. This is repeated K times for each fold, with the mean of these runs serving as the final result. We set K at 10. The first step is to split the data set in half, with 80% going into training and 20% into testing. With each iteration, 90% of the data is used for training and 10% is used for validation. Every model was trained using 30 iterations.

E. CNN-LSTM Model

By merging CNN and LSTM, a new network called the CNN-LSTM network is formed. The first layers use CNN, whereas the subsequent layer employs LSTM. It is possible to use the CNN model to identify the input data's most salient properties. Time series prediction, computational genomics, and natural language processing are some of the applications of LSTM. The detection of grape plant leaf deficiency is achieved by combining the strengths of CNNs and LSTM models. By combining the predictions of the CNN and LSTM, an ensemble method is used to make the CNN-LSTM model more accurate. It all starts with a CNN with n one-dimensional channels in the top layer. Important attributes are chosen using a pooling layer in the subsequent level. Following the LSTM layer, the prediction network is trained using a fully connected layer. At the beginning of the network's development, there may be more than one CNN layer. After preprocessing the whole collected dataset, a CNN-LSTM model—a hybrid of the two—was built. The initial two layers of the method are convolution and max-pooling, and to improve its classification capabilities, an LSTM model has been included.

F. Hyperparameter Setting

Utilising the Adam Optimizer, Stochastic Gradient Descent Optimizer (SGDO), and Root Mean Squared Propagation Optimizer (RMSPO) with learning rates of 0.001, 0.01, 0.1, and 0.2, respectively, the model updated weights and decreased loss. Hyperparameter optimisation makes use of the following optimizers: Adam, SGDO, and RMSPO. In this study, the hyperparameters were established using learning rates of 0.001, 0.01, 0.1, and 0.2. Based on the requested parameter combinations under diverse prediction scenarios, the hyperparameters of the CNN-LSTM model created for this study were optimised using the Optuna framework.

G. A comprehension of Optimizers and How They Work for Weight Updates

Both α1 and α2 are significant first- and second-order estimations that the Adam optimizer takes into consideration. Equations (1) and (2) provide the values of α1 and α2, which may be used to determine the moving averages p and q.

$$p_t = \alpha_1 p_{t-1} + (1- \alpha_1)\, g_t \qquad (1)$$

$$q_t = \alpha_2 q_{t-1} + (1- \alpha_2)\, g_t^2 \qquad (2)$$

Considering the estimations α1, α2, and gradient gt, one may determine the moving averages for a certain iteration t. Most moving average-based calculations, including SGDO and RMSPO, are biassed, therefore fixing the bias requires an extra step. As seen in Equations (3) and (4), this procedure is called bias correction.

$$\hat{p}_t = \frac{p_t}{1- \alpha_1^t} \qquad (3)$$

$$\hat{q}_t = \frac{q_t}{1- \alpha_2^t} \qquad (4)$$

At last, the weights and biases are updated using step size, which is determined by the calculated moving averages using Eq. (5).

$$w_t = w_{t-1} - \eta \frac{\hat{p}_t}{\sqrt{\hat{q}_t} + \varepsilon} \qquad (5)$$

H. An Interpretation with Optimizers and How They Reduce Losses

When building a model, using the right optimizer to lower the gap between estimates and actual data is a top priority. Batch processing the training data is a part of this loss reduction strategy; it delays the overlapping of the parameter values. Adam, SGDO, and RMSPO are just a few examples of optimizers that make parameter changes to the model during training in order to lower a loss function. Consequently, optimizers help reduce total loss and increase accuracy.

IV. RESULTS AND DISCUSSION

The outcomes of the experiments that were conducted using CNN-LSTM are detailed below.

I. Experimental Setting

Classification accuracy improved after applying the proposed CNN-LSTM model to the custom dataset. The suggested ensemble CNN-LSTM model was tested on a dataset consisting of 2095 pictures using Python code and the Spyder development environment. Using the Spyder IDE, we ran the classification model to get the binary classification results. The optimizer and learning rate were two of numerous hyperparameters used during the model training process. The experimental trials included the addition of photographs to split the dataset in half, with 80% of the images going into the training dataset and 20% into the testing dataset. After generating 1800 pictures for the CNN-LSTM model, the code was written in Python and run on the spyder development environment. A combination of convolutional neural network (CNN) and long short-term memory (LSTM) classification models was developed to get comprehensive binary classification results.

J. Analysis

Table IV displays the results and an explanation of those results produced using the CNN-LSTM model. Table IV displays the accuracies attained by the Adam optimizer (98.6%), SGDO (94%), and RMSPO (92%), when the learning rate is set to 0.001. The greatest overall accuracy, at 98.6%, is achieved by the CNN-LSTM model using the Adam optimizer and a learning rate of 0.001. The proposed CNN-LSTM model has an accuracy level between 83% and 98.6%, as shown in Table IV. Levels of accuracy are determined by two hyperparameter settings: the optimizer type and the learning rate. When compared to existing approaches, the suggested CNN-LSTM system is shown in Table V for tabular understanding. See how the CNN-LSTM model stacks up against state-of-the-art techniques in Figure 3.

TABLE IV. FIGURAL DEFINITION OF THE CNN-LSTM MODEL'S OUTCOME

Optimizer	Learning Rate	Accuracy
Adam Optimizer	**0.001**	**98.6**
	0.01	92
	0.1	89
	0.2	85
SGDO	**0.001**	**94**
	0.01	90
	0.1	88
	0.2	84
RMSPO	**0.001**	**92**
	0.01	88
	0.1	85
	0.2	83

TABLE V. COMPARING THE SUGGESTED CNN-LSTM SYSTEM TO EXISTING METHODS VIA TABULAR INTERPRETATION

Model	Accuracy
MLP[11]	74.8
VGG16+RF [8]	87
GA+SVM [3]	90.40
DCGAN [14]	92.60
CNN-LSTM (Proposed)	**98.6**

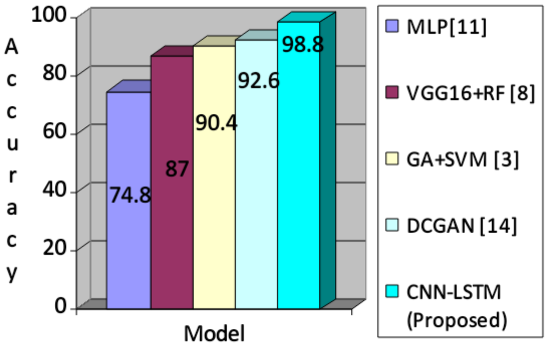


Fig. 3. Visual representation of proposed system compared to current methods

V. CONCLUSION

This work provides a useful tool for identifying nutritional deficiencies in grape plant leaves at an early stage, which may aid farmers in halting the progression of these deficiencies and improving the yield and quality of their crops. The suggested hybrid CNN-LSTM model produced encouraging results for classification accuracy on the self-built dataset. If the CNN and LSTM model can accurately identify nutritional deficiencies in grape plant leaves as N-, P-, K-, Mg-, Ca-, Fe-, Mn-, Zn-, or B-deficiency, then the results are promising. The programme was able to accurately detect nutritional deficiencies in grape plant leaves with a classification accuracy of 98.6 percent. The slow growth of grape plants is caused by illnesses that affect both the grapes and the foliage. Thus, it is crucial to create a computer-based system that can identify nutritional deficiencies in grape plant leaves. Thanks to Deep Learning (DL) techniques, AI can already identify grape leaf deficiencies and store them digitally. It is critical for farmers to diagnose problems quickly so they don't stunt their plants' development or kill them. The development of software that can detect nutritional inadequacies in grape plant leaves would greatly assist farm staff in eliminating these issues more quickly. This study used a convolutional neural network (CNN-LSTM) to train a model for nutritional deficit detection in grape plants. The model classifies photos of sick grape plant leaves into several groups: Deficiency in Nitrogen, Potassium, Calcium, Iron, Manganese, Zinc, and Boron. Changing optimizers and learning rates are two other hyperparameters that may be tweaked for optimal accuracy. Also included in this study are analyses, explanations, and tabulations of the results. At a learning rate of 0.001, the CNN-LSTM model demonstrated its highest level of accuracy while using Adam's optimizer. The most recent approaches are outperformed by CNN-LSTM, which can achieve a maximum accuracy of 98.6 percent. We can build on this work to investigate nutritional deficiencies in more depth in the future. As an extension of this work, it is also possible to study the fraction of leaf area impacted by nutritional insufficiency. Improving the accuracy of the proposed model and investigating its potential use to detect other plant leaf problems may be the topic of future research. Because most soils don't contain enough of the nutrients that plants need, contemporary fertilisation methods include looking for signs of nutrient deficiency in plant leaves. It will be easier to design a fertilisation programme that supplies the right micronutrients while avoiding overproducing others if the amount of vitamins and minerals required is known. Agricultural malnutrition manifests itself in plant leaves via indications of nutritional inadequacy. Physical examination of the plant morphology reveals these symptoms, which are sufficient to diagnose a nutritional deficit. Connected neural networks (CNNs) are used to train the model in this research. A short time later, the LSTM receives the model's output and sorts the leaf photos into healthy, N-, P-, K-, Mg-, Ca-, Fe-, Mn-, Zn-, and B-deficiency categories. The effectiveness of the classifier is evaluated by the accuracy. The results shown that the suggested model achieves an accuracy level of 98.6 percent. These results show that CNNs have great potential as a method for identifying nutritional deficiencies in plant leaves.

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